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Does Graphical Reporting Improve Risk Disclosure? Evidence from European banks

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Does Graphical Reporting Improve Risk Disclosure? Evidence from European Banks

Purpose: This study examines the voluntary disclosure of risk-related issues, with a focus on credit risk, in graphical reporting for listed banks in the major European economies. It aims to understand if banks portray credit risk-related information in graphs accurately and whether these graphs provide incremental, rather than replicative, information. It also investigates whether credit risk-related graphs provide a fair representation of risk performance or a more favourable impression than is warranted.

Design/Methodology/Approach: A graphical accuracy index was constructed. Incremental information was measured. A multi-level linear model investigated whether credit risk affects the quantity and quality of graphical credit risk disclosure.

Findings: Banks used credit risk graphs to provide incremental information. They were also selective, with riskier banks less likely to use risk graphs. Banks were accurate in their graphical reporting, particularly those with high levels of credit risk. These findings can be explained within an impression management perspective taking into account human cognitive biases. Preparers of risk graphs seem to prefer selective omission over obfuscation via inaccuracy. This probably reflects the fact that individuals, and by implication annual report's users, generally judge the provision of inaccurate information more harshly than the omission of unfavourable information.

Research limitations/implications: This study provides theoretical insights by pointing out the limitations of a purely economics-based agency theory approach to impression management.

Practical implications: The study suggests annual reports' readers need to be careful about subtle forms of impression management, such as those exploiting their cognitive bias. Regulatory and professional bodies should develop guidelines to ensure neutral and comparable graphical disclosure.

Originality/Value: This study provides a substantive alternative to the predominant economic perspective on impression management in corporate reporting, by incorporating a psychological perspective taking into account human cognitive biases.

Keywords: banks, corporate reports, impression management, incremental information, omission strategy, credit risk graphs.

Paper type: research paper

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1. Introduction

1 This paper explores the role of graphical reporting in credit risk disclosure by major European listed
2 commercial banks. Lending is the main activity of these financial institutions. Their loan portfolio represents a
3 significant part of their assets and one of the main sources of their income and risk (Ahn & Choi, 2009) with
4 higher levels of credit risk increasing banks' probability of default (Imbierowicz and Rauch, 2014). Unpaid
5 loans decrease banks' profitability, and may result in bank failure. This study seeks to understand how banks
6 portray credit risk-related information and whether they provide incremental, rather than replicative, graphical
7 information in their risk reports. It also investigates whether credit risk-related graphs fairly represent the
8 graph's underlying risk performance or are used for impression management. Risk disclosure is still limited
9 (Abraham and Shrikes, 2014), both in financial and non-financial companies. Banks have different reporting
10 structures compared to non-financial companies (Beattie & Jones, 1997) and follow distinctive regulations and
11 accounting practices (Elshandidy *et al.* 2015). Risk disclosure is crucial for banks as banks are risk-taking
12 enterprises and, especially during the recent credit crunch, this has negatively affected depositors, shareholders
13 and taxpayers (Linsley and Shrikes, 2005; Woods *et al.*, 2008a; Magnan and Markarian, 2011). Risk should be
14 properly managed and publicly disclosed to allow investors and other stakeholders to evaluate banks' risk
15 profile (Linsley and Shrikes, 2005).

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36 Recent research has questioned the usefulness of current risk reporting practice (e.g., Linsley and Shrikes,
37 2005; Woods *et al.*, 2008b; Oliveira *et al.*, 2011a; Bischof and Daske, 2013; Maffei *et al.*, 2014; Elshandidy *et*
38 *al.* 2015; Allini *et al.*, 2016). Risk disclosure has been criticised for not being detailed, nor forward-looking, nor
39 sufficient for assessing the overall risk profile (Linsley and Lawrence, 2007; Magnan and Markarian, 2011) nor
40 relevant for the decision-making process (Beretta and Bozzolan, 2004; Pérignon and Smith, 2010). Moreover,
41 risk-related information reported tends to be 'boiler plate' in nature, difficult to read, lacks comparability and,
42 therefore, is of limited value (Linsley and Lawrence, 2007; Woods *et al.*, 2008a, 2008b; Ryan, 2012).

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52 Ryan (2012) argues companies should present risk disclosures in formats that promote the usability, such as
53 graphs (Beattie and Jones, 2008). Graphs can help users understand banks' risk. They attract reader's attention,
54 facilitate comparisons and identify trends in a readily, 'eye-catching', accessible form (Hill and Milner, 2003;
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Beattie and Jones, 2008). Graphs can be used by annual report's preparers to provide neutral incremental information to the readers. However, graphs in annual reports can also be opportunistically used by managers for impression management (Beattie and Jones, 2008). The concept of impression management originates in social psychology and refers to the practice of presenting information so that it will be perceived favourably by others (Hooghiemstra, 2000). The predominant perspective on impression management in corporate reporting is based on a purely economics-based, agency theory approach (Merkl-Davies and Brennan, 2007). Managers are assumed to be driven by economic rationality, with economic incentives to exploit information asymmetries by providing biased information (Merkl-Davies and Brennan, 2011). In line with this perspective, graphs have been found to be selective (i.e. they enhance positive and de-emphasise negative information) and providing favourable inaccurate and misrepresented information (e.g., Beattie and Jones, 1992; 1999; Mather *et al.*, 1996; Falschlunger *et al.*, 2015). Merkl-Davies and Brennan (2007) suggest that alternative theoretical perspectives, such as a psychological perspective, could explain impression management behaviours in corporate reporting. We explored this by analysing the omission of accounting information (i.e. selectivity) vs commission (i.e. the provision of fabricated or exaggerated information). From an economic perspective individuals do not evaluate the consequences of wrongful (i.e. unfair and biased) omission and commission differently (Baron, 1986). Therefore, managers could either choose selective omission or wrongful commission to provide a more favourable impression of corporate performance. By contrast, a psychological perspective views individuals as having an 'omission bias', i.e. evaluating negative omissions less harshly than wrongful commissions (e.g., Spranca *et al.*, 1991; Cushman *et al.*, 2006). Consequently, like the economics-based perspective, managers might use graphs selectively, by omitting information that does not provide a favourable view. However, in contrast to the economics-based perspective, they might avoid practices of wrongful commission, such as providing inaccurate and misrepresented information, that can cause greater 'condemnation' and public concern (DeScioli *et al.*, 2011a).

The remainder of this paper is structured as follows. In the next section, we discuss the prior literature and develop the hypotheses. In section three, we present our method, including sample selection, data gathering and analysis. In sections four and five, we present findings followed by our discussion and conclusion.

2. Literature Review and Hypotheses Development

2.1. Risk reporting in the banking sector

Risk disclosure is an important part of risk management (BCBS, 2006; Allini et al. 2016). Companies have several incentives for risk disclosures, such as reducing stakeholders' uncertainty, decreasing the cost of capital (Linsley et al., 2006), strengthening their reputation and increasing legitimacy (Oliveira et al., 2011a). Companies also have incentives to decrease risk disclosures harmful to their competitive position (Woods et al., 2008a). Investors benefit from effective risk disclosure as they can compare expected returns with associated risks, thus maximising the utility of their portfolio-investment decisions (e.g. Beretta and Bozzolan, 2004; Linsley and Shrivess, 2005; Abdullah et al., 2015). However, when risk disclosure is generic, qualitative and boiler plate rather than substantive, its utility is limited (Abraham and Shrivess, 2014).

Regulators, standard setters, practitioners and academics have all been concerned with the quality and quantity of risk disclosure (e.g. BCBS, 2006; Companies Act, 2006; Abraham and Shrivess, 2014). There have been calls for a greater and higher-quality transparency in risk reporting in the banking sector, as banks are risk-taking enterprises whose activities have been found, especially during the recent credit crunch, to be unpredictable and unstable (Linsley and Shrivess, 2005; Magnan and Markarian, 2011; Bischof and Daske, 2013). Risk should be properly managed and disclosed by revealing relevant information for investors and other stakeholders (Linsley and Shrivess, 2005). Although banks were the focus of public attention during the recent financial crisis (Erkens et al., 2012), risk disclosure in the banking sector has been under-researched, compared to non-financial firms (Linsley et al., 2006, Maffei et al., 2014).

European banks' risk disclosure is subject to complex regulation by the International Accounting Standards Board, by national central banks and by national and European regulatory bodies, (e.g. the Basel Committee on Banking Supervision, the European Banking Authority). Despite different regulatory bodies imposing greater transparency, no regulatory requirement exists for European banks to include graphs of risk variables (Pérignon and Smith, 2010). Graphical reporting, thus, remains a fully voluntary disclosure choice.

Prior research shows that the level of banks' risk disclosure has increased over time, following an increase in minimum requirements imposed (e.g., Bischof, 2009). However, risk reporting's usefulness for decision-making has not improved at a similar rate (Pérignon and Smith, 2010; Maffei *et al.*, 2014). Recent studies have found risk reporting to be unclear, very general and qualitative, not sufficiently forward-oriented, non-comparable and, thus, unhelpful for the assessment of risk exposure on an on-going basis (e.g., Linsley *et al.*, 2006, Woods *et al.*, 2008a; Oliveira *et al.*, 2011b; Maffei *et al.*, 2014).

The opaqueness and difficulty in interpreting and comparing risk reporting could be reduced by using tables or other well-structured communication formats (Ryan, 2012), such as graphs (Beattie and Jones, 2008).

Studies on graphical reporting and impression management have mainly analysed non-financial firms, excluding financial institutions and commercial banks (Beattie and Jones, 2008), despite the important role graphical reporting can play in presenting understandable risk information by banks.

2.2. *Impression management.*

The dominant perspective in impression management studies in a corporate reporting context is based on economics theories, particularly agency theory (Merkl-Davies and Brennan, 2007). Agency theory focuses on the most efficient contract of governing the relationship between managers and investors, given that both are regarded as rational, self-interested decision-makers (Eisenhardt, 1989). Using this theoretical perspective, previous studies have found that managers used corporate reports opportunistically (Hooghiemstra, 2000). Managers conceal failures and emphasize successes (Courtis, 1998). Individuals can give a false impression of reality by omitting key information (omission) or by purposefully misrepresenting information, either via exaggeration or fabrication (wrongful commission). The distinction between omission and commission is, in itself, not relevant from an economics based impression management perspective, given the same consequences (Baron, 1986). Both omissions and commissions offer a more favourable portrayal of company's performance than is warranted (e.g. Beattie and Jones, 1999; Mather *et al.*, 1996; Falschlunger *et al.*, 2015).

Economics-based hypotheses based on full rationality, however, have limited psychological validity (Merkl-Davies and Brennan, 2007). Individuals make decisions based on limited rationality (Simon, 1955) as, even

when full information is available, their analysis of it is only moderate. Individuals' judgments and choices are influenced by the way in which alternatives are framed (Tversky and Kahneman, 1981). A psychological perspective can thus provide useful insights into corporate graphical reporting strategies.

Psychological studies report that individuals often evaluate omissions and commissions differently. Individuals often evaluate decisions to commit actions (i.e. commissions) more negatively than decisions to omit actions (i.e. omissions), even though either decision could have the same negative consequence. This phenomenon is called 'omission bias' (Spranca *et al.*, 1991). Omission bias seems to be caused by a perceived difference in causality, responsibility, or both (Spranca *et al.*, 1991). As omissions tend to provide less evidence about the intentions of the actor, third parties will tend to be more uncertain about the preparers' intentions for omissions. 'Wrongful' omissions are thus judged less harshly than 'wrongful' commissions (DeScioli *et al.*, 2011b).

Omission bias has several consequences. First, individuals tend to consider harm caused by action as worse than equivalent harm caused by inaction (Cushman *et al.*, 2006). Second, they view omission as less deceptive than commission (Van Swol *et al.*, 2012), even when the actor's intention to deceive is judged to be the same (Haidt and Baron, 1996). As third parties judge omissions less harshly, *ceteris paribus*, then individuals will choose 'wrongful' omissions to incur less blame (DeScioli *et al.*, 2011b). The preference for omission is therefore not necessarily unconscious, but may be strategic. Individuals have been found to choose omission more frequently when there was the possibility of punishment (DeScioli *et al.*, 2011a).

2.3. Hypotheses Development

Public attention to banks' risk management has been very high, given the enormous risks taken by financial institutions at the expense of depositors, shareholders and taxpayers (Linsley and Shriver, 2005; Woods *et al.*, 2008a; Magnan and Markarian, 2011). This public scrutiny has provided incentives for banks to increase transparency on their credit risks, but also to manage disclosures to provide a 'favourable' impression of their credit risk. These incentives are likely to be affected by the current level of credit risk the bank faces.

The economics-based and psychological-based impression management perspectives (e.g., Merkl-Davies and Brennan, 2011) both share the view that riskier banks might not want to release 'negative' news to the public

and consequently will decrease the quantity of voluntary risk disclosures (Abdullah *et al.*, 2015). By omitting information, high risk banks build a 'risk story' (Linsley and Shrivess, 2005: 213) that is favourable to them, simultaneously avoiding public negative reactions.

Despite the lack of neutrality and of comparability of information over time (Beattie and Jones, 2008), given omission bias, annual report users are unlikely to blame preparers as no information is exaggerated or fabricated. Given the importance of credit risk, banks could be selective using credit risk graphs only when they report positive, rather than negative, credit risk. Therefore, we expect that:

H1: Banks are less likely to portray credit risk graphs when they face a higher level of credit risk

Risk reporting's effectiveness and usefulness depends not only on the amount of information provided, but also on the disclosure quality (Beretta and Bozzolan, 2004; Pérignon and Smith, 2010). Textual complexity can obfuscate the adverse information conveyed (Cho *et al.*, 2010). Visual inaccuracies can also serve the same purpose. Inaccurate design can mislead the annual report's readers, with or without an accounting experience (Muiño and Trombetta, 2009; Pennington and Tuttle, 2009). The quality of risk reporting could be affected by the level of risk the bank faces (e.g., Linsley *et al.*, 2006; Maffei *et al.*, 2014).

An economics-based perspective of impression management suggests that managers may engage in wrongful commission by providing an inaccurate and favourable view of corporate performance (Courtis, 1998; Beattie and Jones, 1999; Cho *et al.*, 2012). High risk commercial banks might, therefore, have greater incentives to obfuscate their credit risk performance via inaccurate disclosures to reduce the negative impact of their high riskiness on readers' perceptions. Previous studies have found firms with negative performance were more likely to 'obfuscate' the message, by producing less readable reports (Li, 2008).

However, from a psychological perspective, self-serving annual report's preparers could decide to exploit omission bias. Banks, especially those with a high credit risk, are likely to be subject to high levels of public scrutiny. Managers might avoid practices of wrongful commissions, such as the provision of inaccurate information in the risk report, as the latter can cause greater 'condemnation' and public concern than selective

omissions. In line with a psychological-based perspective of impression management, banks with a high credit risk will therefore be less, rather than more, likely to obfuscate credit risk disclosure. Taking into account the economic-based and psychological-based contrasting view on the influence of riskiness on graphs' accuracy, we expect that:

H2: The level of inaccuracy in banks' credit risk graph is likely to be related to the level of the bank's credit risk

3. Methodology

3.1. Sample and data gathering

We selected the commercial banks based in the largest five European economies (France, Germany, Italy, Spain and the UK) by Gross Domestic Product and listed from 2006 to 2010. We focused on commercial banks as they are the main players in their industry (Oliveira et al, 2011b), have a different activity and risk profile compared to savings and investment banks (e.g. Bischof, 2009; Laidroo, 2016), give weight to credit risk (e.g. Imbierowicz and Rauch, 2014) and have been considered to have high levels of public visibility and scrutiny (Oliveira et al, 2011a) which is likely to affect impression management practices.

Using the database Bankscope, we identified 157 listed banks. We excluded the following: listed subsidiaries of a holding bank already in the sample (20), financial companies that were not commercial banks (75), banks not listed (or whose annual reports were not available) in all the years studied 2006-2010 (15). The final sample comprised 47 commercial banks (235 firm-year observations): 10 French, 9 German, 17 Italian, 6 Spanish and 5 UK banks.

We downloaded the consolidated annual reports from the banks' websites and collected data about all the graphs included in both the risk reports within the management report and in the notes to the financial statements. We call these sections 'risk reports'. To understand whether graphs provided additional information, we also collected all the information related to the variable portrayed in the graph in the five pages surrounding the graph (two pages before and after the graph's page and the graph's page). We chose five pages

as a cut off (Beattie and Jones, 2001; O'Sullivan and Percy, 2004). Data on the bank's risk, stock market performance, profitability, size and audit firm were collected from Bankscope.

3.2. Data analysis

The overall analysis was conducted in two stages. First, we explored the use of credit risk graphs in risk reports and investigated a) whether credit risk graphs portrayed information accurately and b) whether these graphs provided incremental, rather than merely replicative, information. Second, we investigated whether the level of banks' risk influenced the use of credit risk graphs (hypothesis 1) and/or graphs' accuracy/inaccuracy (hypothesis 2).

Both the graphs' accuracy and the extent of the additional information were coded by three researchers. The coding instrument is considered as valid, in terms of well-specified decision categories and decision rules (Beattie and Thomson, 2007), based on previous literature on graphical reporting.

3.2.1. Graphical accuracy

To evaluate the level of graphical accuracy, a set of predefined decision rules was first identified to ensure the reliability of the coding process and measurement and to reduce subjectivity (Marzouk and Marzouk, 2016). Then, three researchers separately applied this set of predefined decision rules to a few cases (10 banks). When any discrepancy between the evaluations was found, it was discussed by three researchers and, if necessary, the decision rules were redefined to make them more stringent and clear. The level of accuracy of all the risk graphs was then evaluated by three researchers who worked independently, with each researcher analysing approximately one third of annual reports. Any discrepancies were discussed by the three researchers and resolved. The few cases of discrepancy were all resolved easily. The level of accuracy was then calculated and the scores for each element of the accuracy index assigned. The self-constructed graph accuracy index incorporates the following aspects considered relevant by the extant literature (Beattie and Jones, 1999; 2008; Hill and Milner, 2003): title of the graph, clarity of the variable portrayed (i.e. clear presence of the variable's name portrayed in the graph's title, key or axes), presence of data values within the graph, presence of X and Y

axes, gridlines, Y axis that begins at zero, and conventional trend. Each item in the index was scored from 0 to

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1. Table 1 includes the details on the scoring procedure.

Insert table 1

For each graph, we calculated a graph accuracy index as the ratio of the sum of the scores awarded to each item divided by the maximum possible potential score achievable by that graph. The total available scores exclude items not applicable to a particular graph.¹ This exclusion, together with the proportional score approach, allows comparable accuracy scores to be constructed for each firm (e.g., Bassett *et al.*, 2007). We then calculated an overall graph accuracy index as the sum of the graph accuracy index for all the graphs inserted in the risk report divided by the total number of risk raphs.

Figures 1 and 2 provide real-life examples of the illustration of different levels of graphs' accuracy for credit risk graphs. Figure 1 represents three credit risk graphs with a high level of accuracy, while Figure 2 represents three anonymised and adapted credit risk graphs with a relatively low level of accuracy.

Insert Figure 1 and Figure 2

3.2.2. Graphical additional information

Risk disclosure is provided in different formats including narrative, tabular and graphical data (Woods *et al.*, 2008b). These reporting formats provide information in different ways, to achieve different purposes (Vessey, 1991), although they may contain similar information. Narratives are appropriate to discuss simple issues and explain particular insights gained through data analysis. Visual representation formats (e.g., graphs) are more appropriate for complex issues (Speier and Morris, 2003) as they require less cognitive effort (So and Smith, 2004). Tables are considered an appropriate format for displaying symbolic information, such as discrete sets of values. By contrast, graphs are deemed to be appropriate for displaying spatial information (i.e. time or cross-sectional comparisons, Vessey, 1991) as they provide additional information beyond the data itself (see Beattie and Jones, 1993).

¹ The graphical accuracy index is composed of three items for pie charts; a minimum of seven and a maximum of eight items for columns, bars and line graphs.

We considered a graph as providing complete additional information (score 1) when no information about the variable portrayed in the graph was reported in the surrounding five pages analysed; as providing partial additional information (score 0.5), when some information was reported and providing no additional information (score 0), when all the information about the variable was reported in the surrounding pages. To evaluate the overall level of additional graphical information in the risk report, we divided the sum of the scores on additional information provided by each graph, by the total number of graphs. Figure 3 provides an anonymised and adapted example, based on real risk reports, of differences in the additional information.

Insert figure 3

3.2.3. Empirical model

To investigate our hypotheses, we developed two different regression models, differing only in terms of the dependent variable. The first model tested hypothesis 1: the dependent variable is the number of credit risk graphs inserted in the risk sections of a bank's annual report (hereafter graph usage).² We employed a multi-level panel regression model containing both fixed and random components. The fixed effects are analogous to the standard regression coefficients and are estimated directly. The random effects take the form of random intercepts (Baum, 2006). In particular, our model tests the influence of our control factors and independent variables, considering bank j at time t , controlling for fixed-year effects (λ_t), country-level random effects $u^{(1)}_i$, and bank-level random effects $u^{(2)}_{j,i}$.

$$(1) \text{ Credit Risk Graphs}_{j,i,t} = \alpha_0 + \beta_1 \text{bank credit risk}_{j,i,t} + \gamma_1 \text{bank size}_{j,i,t} + \gamma_2 \text{profitability}_{j,i,t} + \gamma_3 \text{stock market performance}_{j,i,t} + \gamma_4 \text{audit firm}_{j,i,t} + \lambda_t + Z_{j,i}^{(1)} u_i^{(1)} + Z_{j,i}^{(2)} u_{j,i}^{(2)} + \varepsilon_{j,i,t}$$

In the second regression model, used to test hypothesis 2, the dependent variable is the credit risk's graph accuracy index.

$$(2) \text{ Credit Risk Graph Accuracy index}_{j,i,t} = \alpha_0 + \beta_1 \text{bank credit risk}_{j,i,t} + \gamma_1 \text{bank size}_{j,i,t} + \gamma_2 \text{profitability}_{j,i,t} + \gamma_3 \text{stock market performance}_{j,i,t} + \gamma_4 \text{audit firm}_{j,i,t} + \gamma_5 \text{additional information}_{j,i,t} + \lambda_t + Z_{j,i}^{(1)} u_i^{(1)} + Z_{j,i}^{(2)} u_{j,i}^{(2)} + \varepsilon_{j,i,t}$$

Following previous studies (e.g., Poon and Firth, 2005; Shehzad *et al.*, 2010; Delis and Kouretas, 2011; Lee and Hsieh, 2014), we used two alternative measures to estimate the level of bank credit risk: impaired loans to gross

² In both our dependent variables we used a natural logarithm's transformation to make their potentially skewed distribution more normal.

loans and loan loss reserve to impaired loans. The impaired loans to gross loans ratio assesses the quality of the loans that a bank has on its books and its ability to mitigate credit risk. A higher (lower) ratio indicates a higher (lower) amount of total doubtful loans and thus a higher (lower) risk of non-collection of the amounts due. The loan loss reserves to impaired loans ratio estimates the expected probability of eventual default by loans and the extent to which the total loss is covered. High levels denote a higher probability that potential losses on loans will be covered and a greater ability to mitigate credit risk.

In all regression models, we controlled for the following variables:

Bank size. Larger firms have been found to provide more risk reporting disclosures (e.g. Linsley and Shrides, 2006) and to use more graphs (e.g. Hrasky and Smith, 2008). Bank size was estimated as the natural logarithm of banks' total assets at the end of the financial year.

Financial performance. Higher financial performance provides managers with the incentive to disclose greater information to signal their superior performance to the market (e.g., Wallace and Naser, 1995). Companies typically use more graphs portraying a positive, rather than negative, performance (e.g. Beattie and Jones 1992; Falschlunger *et al.*, 2015). Profitability (the ratio of net income to average equity, ROAE) and stock market performance (the bank's annual stock return) were used to estimate banks' financial performance and measured at the end of the financial year.

Audit firm. High profile audit firms might exert pressure on banks to disclose more data (Bassett *et al.*, 2007) and more accurate risk-related information (Hassan, 2009). This is a dichotomous variable (1 if the annual report was audited by a BIG 4 audit firms, 0 otherwise).

Additional information. Banks might be keener to design a credit-risk graph accurately when the graph provides additional rather than replicative information to that reported in the narratives or tables, as the graph is the only source of information. By contrast, banks could be less accurate in graphical design when the credit-risk graph provides merely replicative information, as the risk report's readers could use narratives or tables to understand that information. This variable is calculated as in paragraph 3.2.2.

4. Results

4.1. Descriptive statistics

Table 2 reports the number of risk-reports with at least one credit risk graph. We identified that 86 out of 235 (37%) risk reports included at least one credit risk graph. Over time, the use of graphs was similar. Each risk report contained, on average, almost 4 graphs (see table 2). We found some evidence of different national patterns: Spanish banks used the most graphs (11.1 graphs per report) while Italian banks the least (1.2 graphs per report). Credit risk graphs were rarely forward-looking: only 2% of graphs portrayed future-related information. Thirty-six percent of the graphs were time-series (see Panel B of Table 2).

We found banks to be highly, although not fully, accurate in risk graphical reporting. The average value of the graph accuracy index was 0.86 out of 1, with some inter-country differences (German banks' graph accuracy index was equal to 0.89, and UK banks to 0.72). Importantly, credit risk graphs did provide substantial additional information as Panel B of Table 2 shows that 74% of the information graphically portrayed was additional, on average.

Insert table 2

Table 3 reports descriptive statistics on banks' characteristics. The average level of a bank's credit risk (i.e. the ratio of impaired loans to gross loans) was 4.6%. This percentage increased markedly over time from 3% in 2006 to 6.4% in 2010. The percentage of loan loss reserve to impaired loans, the other proxy for overall credit risk, was 75.7%. It decreased markedly over time.

Insert table 3

4.2. Multivariate analysis

The correlation matrix (not reported for brevity) shows that the independent variables have correlations lower than |0.6|. The only exception is the correlation between the two proxies used to measure credit risk, the impaired loans to gross loans ratio and the loan loss reserve to impaired loans ratio, that equals -0.73.

The variance inflation factor (VIF) values (reported in table 4) are lower than 5, thus multicollinearity is unlikely to be a concern (Baum, 2006). Table 4 documents our tests of hypotheses. Models 1a and 1b report the multilevel regression used to estimate hypothesis 1 while models 2a and 2b test hypothesis 2. In models 1a and

2a, the impaired to gross loans ratio is used as a proxy to estimate banks' credit risk, while in models 1b and 2b the loan loss reserve to impaired loans ratio is used.

Models 1a and 1b show that banks with higher credit risk portrayed significantly less credit risk-related information ($p < 0.05$). This result is in line with both economic and psychological-based impression management perspectives. Banks selectively omitted credit-risk related information when facing higher credit risk. By contrast, they increased disclosure, by using more graphs, when facing a lower credit risk, thus providing a more favourable view of their results. Thus, H1 is supported.

Models 2a and 2b show that, in line with H2, credit risk affected graphical accuracy. More specifically, banks with higher credit risk were significantly more likely to portray credit risk graphs accurately ($p < 0.05$). These findings provide supports for the psychological-based impression management. In the scenario of high public scrutiny due to the high credit risk, bank's risk report preparers omitted to portray credit risk related graphs, while, at the same time, designing the remaining credit risk graphs more accurately, to avoid negative external reactions.

Banks designed credit risk graphs more accurately when these graphs provided additional information ($p < 0.10$), i.e. they tend to be more accurate when the information portrayed is more relevant, as not reported elsewhere.

Insert table 4

5. Discussion and conclusions

This study has examined graphical risk reporting in European listed commercial banks during 2006-2010. Previous research has assumed that banks have different graphical reporting practices from non-financial firms (e.g., Beattie and Jones, 1997). However, with very few exceptions (e.g. Laidroo, 2016), there has been no empirical study on graphical reporting in banks. Our findings show that graphs portray risk-related information that is not merely replicative, but additional to that reported in narratives and tables in the risk report. In line with previous studies on risk narratives (e.g., Linsley *et al.*, 2006; Oliveira *et al.*, 2011a), the risk information portrayed is rarely forward-looking. The graphs generally also show a high level of accuracy. This finding is in

line with the lack of deliberate obfuscation of bad risk found in annual reports' narratives (Linsley and Lawrence, 2007). Therefore, graphs could potentially be one of those 'well-structured' formats that promote the usability of risk-related information (Ryan, 2012).

However, our study found selectivity in graph's usage and, therefore, a lack of comparability across time. Banks tend to de-emphasise their credit level of risk by omitting graphs, when the risk level is higher. This finding is in line with the prior literature on the 'abuse' of graphs in portraying financial performance (e.g., Beattie and Jones, 1992; 1999; Mather *et al.*, 1996; Falschlunger *et al.*, 2015) as well as in environmental and social performance (Jones, 2011; Cho *et al.*, 2012).

Interestingly, we found banks are more likely to portray credit risk graphs accurately when they face a high, rather than a low, level of credit risk. This seems in contrast with the prior impression management literature, generally based on economics-based theories and mainly analysing nonfinancial companies (e.g., Mather *et al.*, 1996; Beattie and Jones, 1999; Cho *et al.*, 2012). Banks prefer to conceal their bad risk performance through selectivity rather than obfuscate it through an inaccurate use of graphs. Probably, due to the high level of public scrutiny high risk banks face, an inaccurate graphical usage could be spotted and lead to negative external reactions. Therefore, the lack of evidence to support the so-called 'obfuscation' hypothesis (Courtis, 1998) is not necessarily in contrast with impression management, but might be attributed to its limited psychological validity (Merkl-Davies and Brennan, 2007). Individuals tend to have an omission bias, considering 'wrongful' commissions morally worse than 'wrongful' omissions (e.g., Spranca *et al.*, 1991; Cushman *et al.*, 2006). In a corporate reporting context, annual report's preparers might (subconsciously or consciously) be aware of this cognitive bias and adopt an omission strategy, to avoid public negative reactions and to manage readers' impressions. High risk banks appear to choose 'wrongful' omissions (i.e. the selective omission of graphical information), but avoid 'wrongful' commissions, (i.e. inaccurate graphical information), to potentially avoid the external concern and potential blame derived from an inaccurate misrepresentation. Thus, in contrast to the prior studies analysing non-financial companies (e.g. Beattie and Jones, 1999; Falschlunger *et al.*, 2015), impression management practices of omission (selectivity) and inaccurate wrongful commissions do not seem complementary.

1 As in any study, our study has some limitations. First, although credit risk is the main risk faced by commercial
2 banks, there are potentially other banking risks (i.e. market and liquidity risks), which could affect graphical
3 voluntary disclosure. Future studies could try to examine their influence on graphical reporting within risk
4 reports. Second, our sample covered most of the major and important European commercial banks (Financial
5 Stability Board, 2011), however future studies could explore graphical reporting by investment, savings and
6 cooperative banks. Third, future studies could investigate whether narratives and other presentational formats
7 (e.g., photos) substitute or complement risk graphs. Finally, more research into the usefulness and value
8 relevance of graphical risk disclosure, from a user's perspective, is welcomed. There are therefore promising
9 opportunities for future research in this under-investigated area.
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19 This study nonetheless provides valuable theoretical insights and has relevant practical implications. It points
20 out the importance of including psychological perspectives on impression management literature in the
21 corporate reporting context. Annual report readers need to be careful about subtle forms of impression
22 management, such as the ones that exploit their cognitive biases. More specifically, analysts and investors
23 should pay close attention when comparing the risk disclosure of banks with different levels of risks.
24 Regulatory bodies should consider guidelines or checklists for neutral and comparable graphical disclosure, to
25 prevent annual report preparers opportunistically exploiting the latitude in graphical voluntary disclosure
26 choices. We also suggest professional bodies educate the main users of financial information (e.g. analysts) on
27 the presence of potential cognitive biases within the decision-making. Education has been found useful in
28 mitigating the decision-biasing effects of misleading graphs (Raschke and Steinbart, 2008) and we argue that it
29 can be useful in making the user alert and aware of the omission bias. Finally, professional bodies can provide
30 incentives (e.g. annual report awards) to annual reports' preparers for neutral voluntary disclosures, as
31 incentives might mitigate impression management practices.
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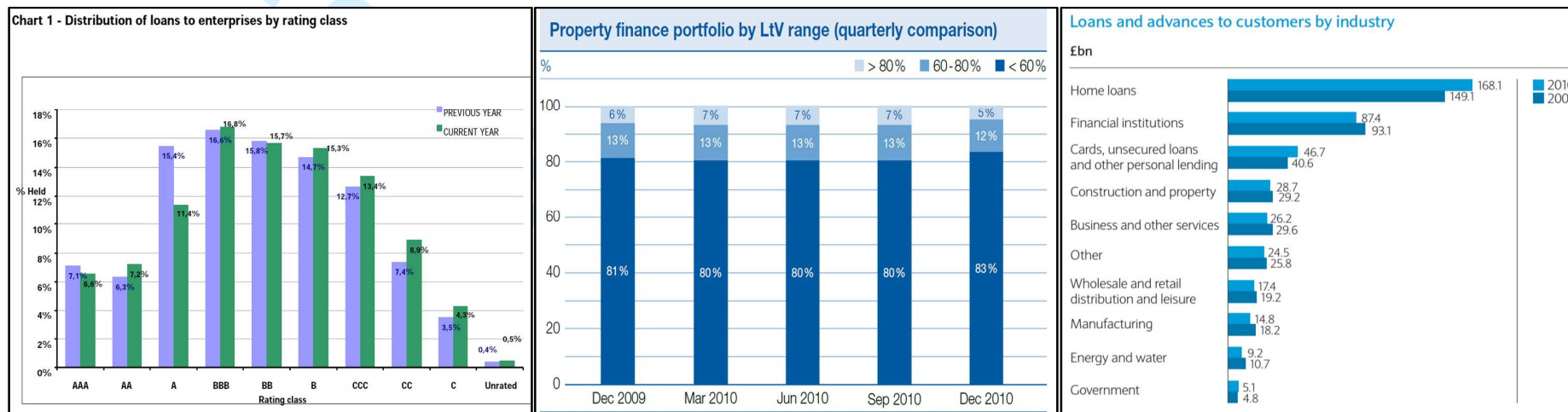
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Figure 1: Real-life examples of accurately designed credit risk graphs.

2009 Credito Valtellinese annual report, p.222

2010 Aareal Bank annual report, p. 91

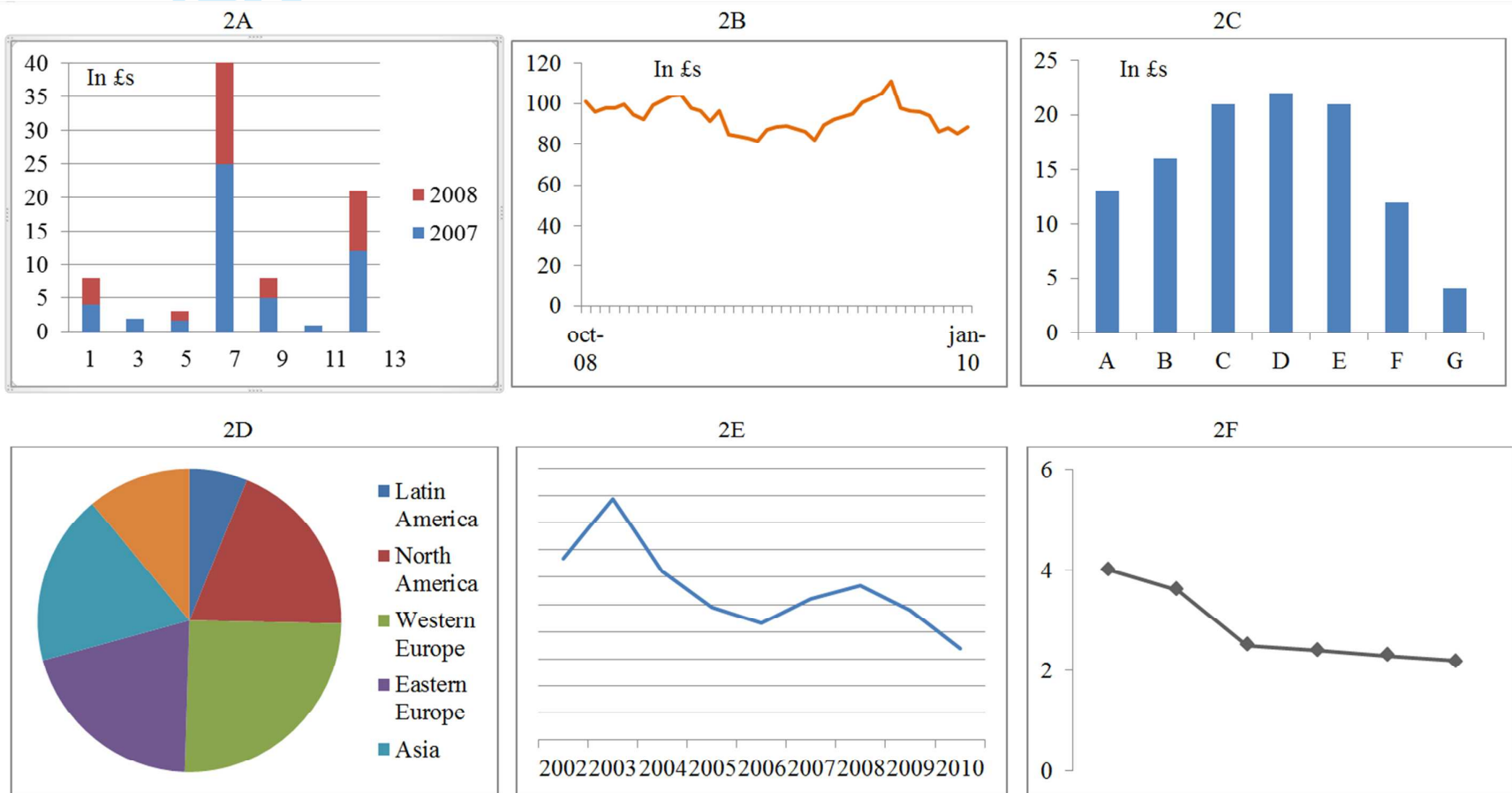
2010 Barclays annual report, p. 90



Permissions to reproduce the original graphs have been obtained by the companies. We are extremely grateful to the companies for this.

The three graphs are all accurately designed with: title of the graph, variables clearly identified, x and y axes clearly numerically labelled and with clearly displayed units of measurement, zero-origin, gridlines (except the third graph), and conventional order. The graph accuracy index equals 1 for the first two graphs, 0.875 for the third graph.

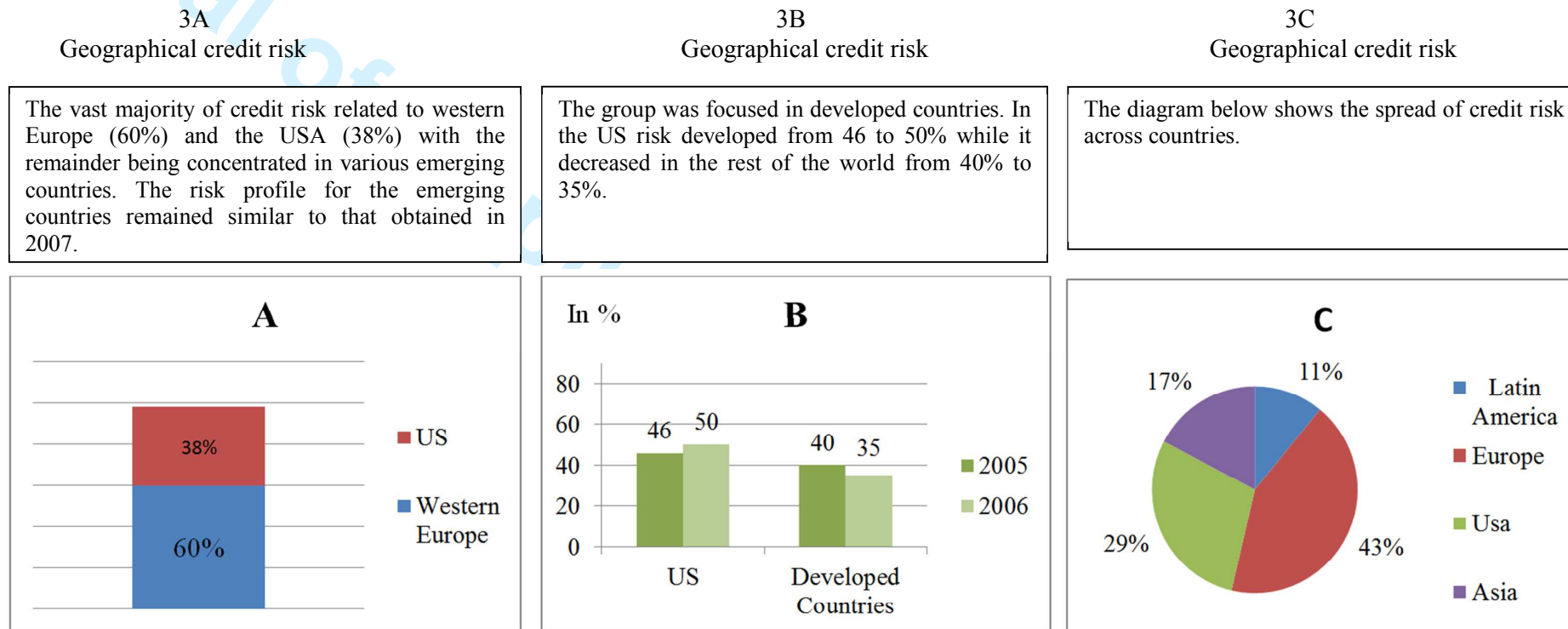
Figure 2: Anonymised and adapted real-life examples of inaccurately designed credit risk graphs.



These graphs suffer from several design problems: they often have problems such as no title, the variable is not easily identifiable, gridlines and data are often missing. The graph's accuracy index is lower than 0.6.

Note: the information contained in this graph is for illustrative purposes only and is not intended to be representative of any specific financial product, project, institution or individual.

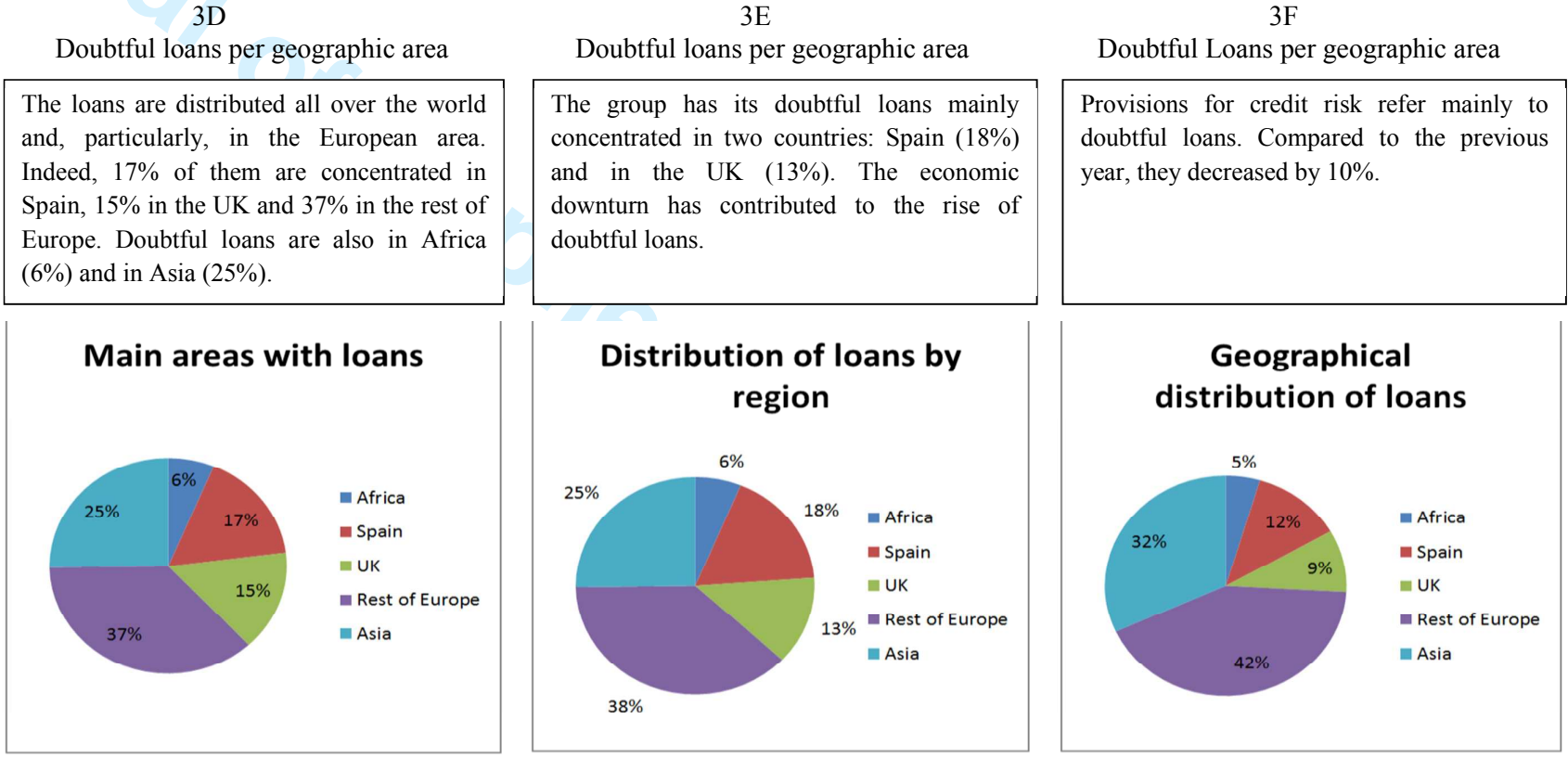
Figure 3 (panel A): Anonymised and adapted but real-life examples of graphs with no additional information (left), partial additional information (middle) and full additional information (right).



The three graphs refer to the distribution of credit risk by geographic area. The graph on the left does not portray any additional information, as the same data are included in the text. The risk report would have provided the same amount of information even without the graph. The graph in the middle portrays partial additional information, as the text provides the same information for the US area but less precise information for the United Kingdom, Europe and the Rest of the World. By contrast, the graph on the right portrays full additional information, compared to the information included in the five surrounding pages.

Note: the information contained in this graph is for illustrative purposes only and is not intended to be representative of any specific financial product, project, institution or individual.

Figure 3 (panel B): Anonymised and adapted but real-life examples of graphs with no additional information (left), partial additional information (middle) and full additional information (right).



The three graphs refer to the distribution of doubtful loans by geographic area. The graph on the left does not portray any additional information, as the same data are included in the text. The graph in the middle portrays partial additional information, as the text provides the same information for two countries (Spain and the UK) but no information for the other regions. By contrast, the graph on the right portrays full additional information, compared to the information included in the five surrounding pages.

Note: the information contained in this graph is for illustrative purposes only and is not intended to be representative of any specific financial product, project, institution or individual.

Table 1: Graphical accuracy index

Item	Importance	Score	Applicable to
1. <i>Title of the graph</i>	Provides the overall message the firm is conveying	<ul style="list-style-type: none"> ▪ 1 if the graph contained a title; ▪ 0 otherwise. 	All graphs
2. <i>Clear variable</i>	Increase accuracy when readers can easily understand the variable(s) portrayed.	<ul style="list-style-type: none"> ▪ 1 if it was possible to understand the variable portrayed in the graph from either the graph's title, key or axes), without reading other information contained in the risk report; ▪ 0 otherwise. 	All graphs
3. <i>Data within the graph</i>	The presence of numbers attached to the graph's specifiers, or to the relevant points of a line graph, provides the reader with precise quantitative values.	<p>For columns and pie charts:</p> <ul style="list-style-type: none"> ▪ 1 if there was a number attached to every individual specifier; ▪ 0.5 if there was a number attached to some of the specifiers; ▪ 0 otherwise. <p>For line graphs,</p> <ul style="list-style-type: none"> ▪ 1 if there were numbers attached to either the maximum and minimum points or to the initial and final points of the line; ▪ 0 otherwise. 	All graphs
4. <i>X axes</i> 5. <i>Y axes</i>	Increase accuracy when axes are clearly numerically labelled and show the measurement unit	<ul style="list-style-type: none"> ▪ 1 if axes were properly numerically labelled and specified the units of measurement; ▪ 0.5 if axes were either properly numerically labelled or specified the units of measurement; ▪ 0 otherwise. 	All but pie charts
6. <i>Gridlines</i>	Help a reader to identify the quantitative values that are some distance from the baseline.	<ul style="list-style-type: none"> ▪ 1 if the graph contained gridlines; ▪ 0 otherwise. 	All but pie charts
7. <i>Zero axis</i>	Its omission could be opportunistically used to misrepresent information.	<ul style="list-style-type: none"> ▪ 1 if the graph had a zero origin; ▪ 0 otherwise. 	All but pie charts
8. <i>Conventional trend</i>	Unconventional trends make it more difficult to perceive the trend line.	<ul style="list-style-type: none"> ▪ 1 if the time series was conventionally ordered (left to right or top to bottom) ▪ 0 if the time series was unconventionally ordered (right to left or bottom to top). 	Time series

Table 2: Number and characteristics of credit risk graphs in each risk-report (average values)

Panel A: Number and percentages of risk-reports with at least one credit risk graph

	All	Country					year				
		France	Germany	Italy	Spain	UK	2006	2007	2008	2009	2010
% of risk-reports with at least one credit risk graph	37%	26%	60%	19%	73%	32%	34%	40%	36%	34%	40%
Number of credit risk graphs portrayed per risk-report	3.63	2.68	4.58	1.21	11.13	3	3.15	4.47	3.98	3.11	3.43
Credit risk graphs by type (Number per risk-report)											
Bar	0.43	0.00	1.42	0.05	0.40	0.84	0.32	0.81	0.57	0.23	0.21
Line	0.57	0.00	0.73	0.04	3.13	0.16	0.83	0.91	0.43	0.32	0.36
Column	1.20	0.86	0.76	0.52	4.03	1.60	1.00	1.13	1.21	1.28	1.38
Pie charts	1.40	1.82	1.67	0.61	3.40	0.40	0.94	1.60	1.77	1.26	1.47
Other types	0.02	0.00	0.00	0.00	0.17	0.00	0.06	0.02	0.00	0.02	0.00

Panel B: only risk reports with at least one credit risk graph

Credit risk graphs with forward-looking information (%)	2%	0%	0%	0%	6%	0%	8%	4%	0%	0%	0%
% of credit risk graphs with time series (%)	36%	22%	36%	8%	40%	79%	39%	37%	33%	36%	34%
Graph accuracy index	0.86	0.88	0.89	0.86	0.88	0.72	0.88	0.85	0.86	0.86	0.88
Additional information	0.74	0.74	0.70	0.76	0.78	0.71	0.74	0.75	0.74	0.75	0.73

Table 3: Company's characteristics

Panel A: Whole sample										
	Mean	Median	Standard deviation	Min.	Max.					
Credit risk (impaired loans/gross loans in %)	4.6	4.0	3.3	0.1	17.2					
Credit risk (loan loss reserve /impaired loans)	75.7	61.4	62.6	18.4	452.0					
Bank size (total assets in millions €)	378,440.0	44,000.0	612,566.0	248.0	2,600,000.0					
Profitability (ROAE, in %)	8.8	9.3	11.2	-86.7	46.2					
Stock Return (in %)	-7.7	-9.9	42.3	-92.6	206.9					
Audit firm (in %)	79.0	100.0	41.0	0.0	100.0					
Panel B: Country and year-analysis (mean values)										
	France	Germany	Italy	Spain	UK	2006	2007	2008	2009	2010
Credit risk (impaired loans/gross loans in %)	5.9	3.6	5.3	2.9	3.6	3	3.3	4	6	6.4
Credit risk (loan loss reserve /impaired loans)	62.8	55.0	63.9	153.6	61.2	109.8	97.5	64.1	57.9	54.4
Bank size (total assets in millions €)	517,350	331,870	84,185	293,533	1,286,800	309,808	375,520	417,420	387,700	401,751
Profitability (ROAE, in %)	8.7	7.3	7.3	13.7	10.2	14.4	14.7	2.5	5.8	6.6
Stock Return (in %)	-5.2	2.8	-11.8	-14.9	-9.3	14.8	-17.2	-50.6	23.8	-8.7
Audit firm (in %)	80	89	65	100	80	79	79	79	79	79

Table 4 –Relationship between bank's credit risk and credit risk graph usage and accuracy.

	Model 1a ^(a, b)	Model 1b ^(a, b)	Model 2a ^(a, b)	Model 2b ^(a, b)
Dependent variable	<i>Graph usage</i>	<i>Graph usage</i>	<i>Graph accuracy</i>	<i>Graph accuracy</i>
Impaired loans to gross loans ratio	-2.14 **		2.14 **	
Loan loss reserve to impaired loans ratio		2.04 **		-2.51 **
Bank size	2.59 **	2.69 ***	-2.89 ***	-2.83 ***
Profitability	-0.01	0.30	1.37	1.08
Stock market performance	-0.36	-0.71	-1.34	-1.22
Audit firm	0.38	0.23	1.19	1.32
Additional information			1.76 *	1.80 *
year 2007	0.63	0.65	-0.56	-0.73
year 2008	0.24	0.15	-0.82	-1.19
year 2009	0.41	0.15	-1.04	-1.24
year 2010	0.46	0.11	-0.83	-0.93
Constant	-1.77 *	-2.75 ***	7.36 ***	7.57 ***
No obs	197	194	79	78
Mean VIF	1.75	1.71	1.87	1.91
Max VIF	2.55	2.61	2.92	3.17
Wald chi ²	18.58 ***	18.20 ***	22.25 **	23.71 ***
LR test (chi ²)	213.83 ***	206.99 ***	65.05 ***	66.59 ***

Note: The table presents the z-values.

(a) Country-level random effects and bank-level random effects are included in the models.

(b) In model 1a, we lost 37 observations because there were no disclosed data on the impaired loans to gross loans ratio, and one observation because of missing data on the stock market performance. In model 1b, we lost 40 observations because there was no disclosed data on the loan loss reserve to impaired loans ratio and one observation because of missing data on the stock market performance. In model 2a, our subsample starts from 86 observations (number of reports with at least one credit risk graph). Then we lost 6 observations because the lack of data on the impaired loans to gross loans ratio and 1 observation because of missing data on the stock market performance. In model 2b, we lost 7 observations because there was no disclosed data on the loan loss reserve to impaired loans ratio and 1 observation because of missing data on the stock market performance.

*, **, *** denote difference is significant at the 0.10, 0.05 and 0.01 level respectively.